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Mapping relative social vulnerability in six mostly urban municipalities in South Africa

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ABSTRACT

Urban decision-makers in South Africa face growing challenges related to rapidly expanding populations and a changing climate. To help target limited resources, municipalities have begun to conduct climate change vulnerability assessments. Many of these assessments take a holistic approach that combines both physical hazard exposure and the underlying socio-economic conditions that predispose populations to harm (i.e., social vulnerability). Given the increasing use of socio-economic conditions in climate change vulnerability analyses, this paper seeks to explore two key research questions: 1) can the spatial distribution of relative social vulnerability be estimated in six mostly urban South African municipalities, and if so, 2) how sensitive are the results to a range of subjective methodological choices often required when implementing this type of analysis. Here, social vulnerability is estimated using socio-economic and demographic data from the 2001 and 2011 South African censuses. In all six municipalities, social vulnerability varies spatially, driven primarily by differences in income, assets, wealth, employment and education, and secondarily by differences in access to services and demographics. Even though social vulnerability is estimated from a wide array of population characteristics, the spatial distribution is surprising similar to that of the percent of working-age individuals making less than 800 rand per month. Areas with high percentages of previously disadvantaged, extended family, and informal households tend to display relatively higher levels of social vulnerability. In fact, demographics (e.g., race, language, age) are often highly correlated with other characteristics that have direct ties to social vulnerability (e.g., income, employment, education). The spatial patterns of relative social vulnerability are similar in 2001 and 2011. However, there is some evidence social vulnerability is relatively lower in 2011. While the choice of input data and aggregation method can affect the spatial distribution of social vulnerability, the general spatial patterns appear to be fairly robust across a number of subjective choices related to methodological and aggregation approach, spatial resolution, and input data.

1. Introduction

Urban decision-makers in South Africa face growing challenges related to rapidly expanding populations and a changing climate. In South Africa, urban municipalities house more than half of the South African population and generate more than 80% of the country's economic activity (van Huyssteen, Oranje, Robinson, & Makoni, 2009; 2015). Between 1996 and 2011, urban populations grew at an annual rate of 3% (le Roux, Gerbrand, van Huyssteen, & van Nierkerk, 2018), a rate that is unlikely to subside in the near future. Unfortunately, urban municipalities, like many other areas in South Africa, remain dominated by the residual effects of the spatial planning legacy of apartheid. This has resulted in significant spatial variations in social inequalities (le Roux, Khuluse, & Naude, 2015; van Huyssteen et al., 2009; 2013), variations that are often re-enforced by the dynamic, often unplanned growth in urban municipalities (van Huyssteen, le Roux, & van Niekerk, 2013). At the same time, Southern Africa is extremely vulnerable to climate variability and change (e.g., Davies, Midgley, & Chesterman, 2010; Niang et al., 2014), as exemplified by the 2017–2018 water crisis in Cape Town.

Urban areas are incredibly complex systems that resist easy interpretation and analysis, including when it comes to climate change vulnerability (e.g., Archer et al., 2014; Dodman & Satterthwaite, 2008; Leck & Roberts, 2015; Romero-Lankao & Qin, 2011; Tapia et al., 2017). Fortunately, the literature exploring the drivers and underlying causes of vulnerability in urban municipalities has increased significantly in recent years, including in South Africa (e.g., Archer et al., 2014; Broto, Boyd, & Ensor, 2015; Gu et al., 2018; Leck & Roberts, 2015; Lee, 2014; Pelling & Wisner, 2009; Roberts & O'Donohue, 2013; Romero-Lankao & Qin, 2011). This growing body of literature provides insights into how

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best to explore and interpret vulnerability in urban areas.

While there are a number of competing definitions of vulnerability, generally speaking, it can be viewed as the potential to suffer loss or harm (e.g., Cutter, 1996). The concept of vulnerability to climate change is not new and has been reviewed extensively (e.g., Alwang, Siegel, & Jørgensen, 2001; Cutter, Emrich, Webb, & Morath, 2009; Füssel & Klein, 2006; Hinkel, 2011; Nelson, Kokic, Crimp, Meinke, & Howden, 2010; Preston, Yuen, & Westaway, 2011; Tate, 2012; Wisner, Blaikie, Cannon, & Davis, 2004). These previous studies provide an excellent summary of how different fields have approached and defined vulnerability, as well as a number of conceptual models for assessing vulnerability. As noted by numerous authors, conceptual models for vulnerability have evolved over the past decades to the point where social, economic, and cultural factors are recognized as being as important as biophysical factors (e.g., Cutter, Boruff, & Shirley, 2003; Füssel & Klein, 2006; Lee, 2014; Preston et al., 2011). However, this rich literature also demonstrates that operationalizing any of these vulnerability frameworks is extremely difficult (e.g., Hinkel, 2011; Nelson et al., 2010). Given the practical challenges associated with operationalizing conceptual frameworks, it has been suggested that the development of quantitative indicators of vulnerability may not be scientifically sound or policy relevant and that these indicators can be misleading at best (e.g., Hinkel, 2011; Klein, 2009). While this discussion is ongoing, it is beyond the scope of this paper to review this vast and growing body of literature. Instead, the practical assumption is made that decision-makers will continue to request ways to differentiate and identify vulnerable populations, and thus there will be a continued application of the vulnerability frameworks available. Therefore, there is a need to continue to explore the utility and robustness of these frameworks.

This paper adopts the climate change risk framework articulated in the most recent reports from the Intergovernmental Panel on Climate Change (IPCC, 2014). This framework expresses risk as a function of exposure to a hazard and the underlying vulnerability of a system. Within this framework, vulnerability can be viewed as the inherent characteristics that predispose a system to harm. An increasingly common approach to approximate these characteristics is through the concept of social vulnerability (e.g., Cutter et al., 2003; Tate, 2012; 2013). As an emergent quality, social vulnerability is virtually impossible to measure (e.g., Moss, Brenkert, & Malone, 2001; Patt, Schroter, de la Vega-Leinert, & Klein, 2008; Tate, 2012) but can be approximated in a number of ways. One of the more widely used methodologies is the Social Vulnerability Index (SoVI), which was first developed for counties in the United States (e.g., Cutter, 1996; Cutter et al., 2003), but has since been used by a growing body of literature (e.g., Burton & Cutter, 2008; Cutter, Ash, & Emrich, 2014; de Sherbinin & Bardy, 2015; Fekete, 2011; Finch, Emrich, & Cutter, 2010; Gu et al., 2018; Hung, Wang, & Yarnal, 2016; Lujala, Lein, & Rosvoldaune, 2014; Rygel, O'Sullivan, & Yarnal, 2006; Tate, Cutter, & Berry, 2010; Wood, Burton, & Cutter, 2010). This methodology takes a place-based approach, which recognizes that vulnerability emerges out of location specific contexts (e.g., Cutter, 1996; Cutter et al., 2003). Social vulnerability indices, like other vulnerability indices, are of interest to decision-makers as they purport to identify communities and populations that are relatively more vulnerable than others (e.g., Birkmann, 2006).

The SoVI has been applied to locations around the world (e.g., de Sherbinin & Bardy, 2015; Gu et al., 2018; Letsie & Grab, 2015; Lujala et al., 2014; Mazumdar & Paul, 2016), including in South Africa (e.g., le Roux et al., 2018, 2015; City of Tshwane, 2015). le Roux et al. (2015) developed a South Africa-wide SoVI using 14 different variables from the 2011 South African census. This work helped identify hotspots of social vulnerability across South Africa. However, given the vast socioeconomic differences within South Africa, a national SoVI can unintentionally conflate urban and rural vulnerability. For example, a certain level of income might lead to very different levels of vulnerability in rural and urban areas given the different costs of living. Informal employment and natural assets may also factor differently into vulnerability in rural and urban areas. Beyond the pioneering work of le Roux et al. (2015), several South African urban municipalities, including Cape Town, eThekwini, Tshwane, and Johannesburg, have begun conducting climate change vulnerability assessments. Increasingly these assessments are incorporating both physical hazards and social vulnerability (e.g., City of Tshwane, 2015). To support these ongoing efforts, this paper seeks to address two key research questions: 1) can the spatial distribution of relative social vulnerability be estimated in six mostly urban South African municipalities, and if so, 2) how sensitive are the results to a range of subjective methodological choices often required when implementing this type of analysis.

2. Methodology

2.1. General methodology

Socio-economic and demographic data were extracted from the 2001 and 2011 South African censuses (Stats SA, 2011; 2015) for six mostly urban municipalities: the City of Cape Town, Nelson Mandel Bay (i.e., Port Elizabeth), Buffalo City (i.e., East London), eThekwini (i.e., Durban), the City of Johannesburg, and the City of Tshwane (i.e., Pretoria) (see Fig. 1 for municipal locations within South Africa). The next full census will not be conducted until 2021, so the 2011 survey is the most recent comprehensive data set available. This data was obtained either at the individual or household level (Annex 1, Table A1). For most data, information was extracted for a single variable (e.g., population group, language, cell phone ownership). However, in some cases (e.g., education, employment), the variable of interest was paired with the age of the respondent to garner information more relevant to the concept of social vulnerability. For example, employment levels for individuals between 25 and 65 years of age are likely more relevant to social vulnerability than employment data for all age groups, which could include large school-age or retired populations.

For the 2011 census, data was extracted for three sets of sub-municipal administrative boundaries: ward, sub-place, and small area, while data was only extracted for one set (i.e., sub-place) for the 2001 census. The number of sub-municipal administrative units increases going from the ward to the sub-place to the small area level (e.g., Table 1). While generally similar in number and location, the sub-place administrative boundaries changed somewhat between the 2001 and 2011 censuses. Similarly, the data collected in the two censuses were not identical. However, where possible, identical data was extracted from both censuses (see Annex, Table A2). The lack of identical data and differences in sub-place administrative boundaries makes direct comparisons across the two censuses difficult. These challenges are addressed further in section 3.1.2.

All of the data extracted from the censuses were evaluated for their relevance and likely contribution to social vulnerability (see next section for detailed discussion). Following Cutter et al. (2003) social vulnerability was broadly defined and was not associated with a specific climate stressor. A number of the variables could be framed as either reducing (e.g., well-educated, wealthy, employed) or increasing (e.g., limited education, poor, unemployed) vulnerability. In many cases, data were extracted to capture both aspects (see Table 2). This was done both because, for example, a high percentage of high income individuals is not the direct inverse of a high percentage of low income individuals, and because capturing both aspects allowed the sensitivity of the results to the input data chosen to be examined. Once all of the variables were extracted, they were subjectively divided into nine categories. These subjective categories can help one quickly identify which aspects of social vulnerability are and are not captured by the census data. However, they were not used during the primary analysis of the data (i.e., the principle component analysis), and were only employed during the sensitivity analysis where an additive model was

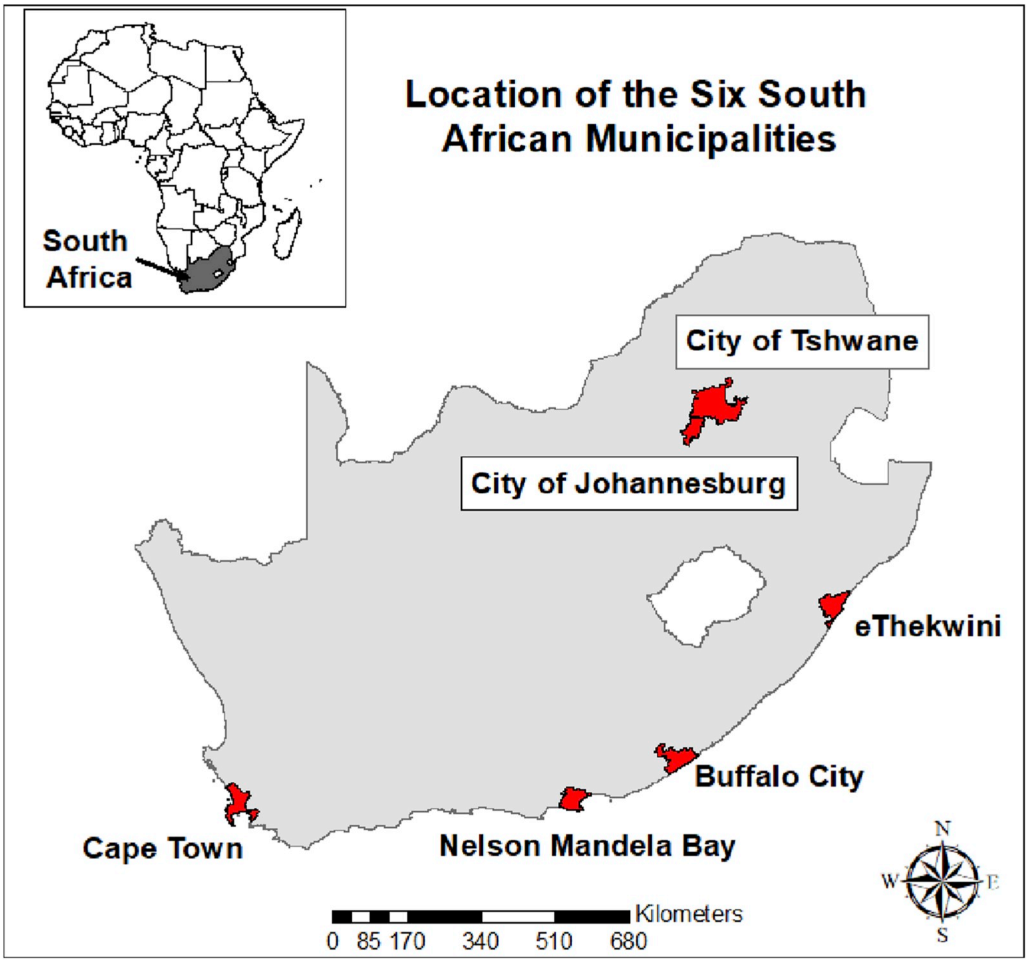

Fig. 1. Location of South Africa (inset) and location within South Africa of the six mostly urban municipalities examined in this study (main map).

Table 1
Number of administrative units for each urban municipality for the 2011 census.

Urban area	Ward	Sub-place	Small Area
City of Cape Town	111	921	5338
Nelson Mandela Bay	60	250	1806
Buffalo City	50	347	1386
eThekwini	104	674	4791
City of Johannesburg	130	804	5800
City of Tshwane	105	594	4524
All urban areas except Tshwane	455	2996	19,171
All six urban areas	560	3590	23,645

used to aggregate the data (see Section 3.2.5). While some of the variables used have clear ties to vulnerability (e.g., income, assets, education), others have a less direct conceptual tie (e.g., demographics, household status, other). As it was impossible to determine a priori the way in which some of the variables would affect social vulnerability, the variables were not inverted or otherwise manipulated in an attempt to place them all on a similar good-bad numerical scale. As the analytical approach used is based on linear correlations, not inverting data should not have a significant impact on the results. However, not inverting the data does require examination of the sign of the variable when it is weighted on to a component. As noted below, all of the variables were normalized onto a 0–1 scale.

Administrative units with small populations (i.e., less than 40

Table 2
Variables Used. For definitions of each variable see Annex, Table A1.

Category	Variables
Income	Low Income, Average Annual Income, High Income
Assets	Computer, Car, Satellite TV, Cell Phone, Internet from Home, No Internet
Education	Poor Education, Good Education, School Attendance
Employment	Head of Household Employed, Working Age Employed, Working Age Unemployed
Services	Flush Toilet, Piped Water Inside Dwelling, Cooking Fuel, Trash Removed, Access to City Water, Lighting Source, Mail Delivered
Heath	Communication Difficulty, Mental Difficulty, Physical difficulty, Self-Care Difficulty
Household	Population Density, Average Household Size, Households with > 6 people, Informal Dwellings, Female Headed Households, Non-Core Family Members, Father Alive, Mother Alive
Demographics	***Age:*** Under 5 or Over 65, Under 5, Over 65, Average Age, Median Age, ***Race:*** Black, Coloured, Indian/Asian, White, ***Language:*** Afrikaans, English, IsiXhosa, IsiZulu, Any African Language, African Language that is not IsiZulu or IsiXhosa, Other Language
Other	Housing Rented, Housing Rent Free, Non-Citizen, Moved since the Last Census, Recent Arrival

people) or only a few households (i.e., less than eight households) were initially excluded from the analysis. While these thresholds are arbitrary, it was assumed that the robustness of data for administrative units with small sample sizes could be relatively lower than for administrative units with large sample sizes. For example, small errors in data collection would more strongly bias the statistics used for administrative units with small sample sizes relative to those with large samples sizes. Furthermore, areas with small populations are less likely to be a focus for policy makers. Administrative units where the enumeration area type was more than 90% industrial, commercial, park, vacant or collective living quarters were also removed from the analysis owing to the difficulty of accurately capturing population characteristics in such areas. Data from the remaining administrative units were then linearly normalized on a scale of 0–1. During normalization outliers were identified as administrative units where the value exceeded two standard deviations of the mean. These outliers were not included in the normalization process to avoid biasing the results, but instead were given either the maximum (1) or minimal value (0) depending on which side of the mean they fell. As the SoVI is a relative measure, administrative units with anomalously high or low values could bias how that variable is included within the analysis (e.g., it could skew the linear correlations between variables). The impacts on the resultant social vulnerabilities of these subjective choices were examined through the sensitivity analysis.

The normalized data were then analyzed using Principal Component Analysis (PCA) within the SPSS© computer software. Within the PCA, the correlation matrix was used for data extraction and Varimax rotation was applied to reduce the number of components onto which each variable was loaded. Only those components with an eigenvalue greater than one were retained. The retained components were then determined to either contribute to or mitigate social vulnerability. This was done both visually (i.e., visual inspection of the variables loaded onto each component), and though an automated program written in MATLAB© (see detailed explanation in Section 2.2). Once the contribution potential (i.e., the potential to contribute to or mitigate social vulnerability) of each component was determined, the relative social vulnerability of an administrative unit was estimated by adding the components together. During aggregation, the components were weighted by the percent of the variance they explained within the PCA.

The analysis outlined above was conducted for each municipality at each spatial resolution using 15 (2011) or five (2001) different subsets of the input variables (Annex 1, Table A2). Only five data subsets were analyzed for 2001 given the relative insensitivity of the general spatial patterns of social vulnerability to the input data found using the 2011 data (see section 3.2 below). These data subsets should not be seen as mutually exclusive, but merely different ways to approximate social vulnerability. Therefore, while some subsets used completely distinct variables, others included overlapping variables. Similarly, some subsets included demographic data, while others did not. However, in all data subsets an attempt was made to ensure a diverse range of the categories outlined in Table 2 was captured. Unless noted otherwise, the results presented below are for the average vulnerability computed across all data subsets used.

Here an averaging approach was deemed appropriate as it was not possible to determine which data subset was inherently more representative of social vulnerability than the others. This study sought to both estimate a robust sense of the relative social vulnerability of administrative units, as well as identify those administrative units where the resultant social vulnerability was particularly sensitive to the input data used. However, it is important to note that these values are not true averages as the social vulnerability calculated for each data subset is relative only to other values within that data subset. However, the general results and conclusions from this analysis are unchanged if the vulnerabilities from each data subset are first placed into quintiles (see below) and then those quintiles are averaged across the data subsets. This is likely owing to the fact that generally speaking the social vulnerability estimated for most administrative units was similar across the data subsets and the ranges of vulnerabilities were similar for all data subsets. There is no perfect measure of the "average" social vulnerability of an administrative unit. However, the averages used were considered a more robust estimation of relative social vulnerability of an administrative unit than the vulnerability estimated from a single data subset.

Previous studies have noted that social vulnerability assessments are based on a number of subjective choices (Tate, 2012, 2013 and reference therein). Therefore, the sensitivity of the results to the 1) data preparation and analysis technique, 2) variables used, 3) spatial extent of analysis, 4) spatial resolution of data, and 5) aggregation technique was examined. While this sensitivity analysis is not as robust as some (e.g., Tate, 2012), it is an attempt to ensure that the results are at least internally self-consistent and not overly sensitive to these subjective choices. Given the relative insensitivity of the general spatial patterns of social vulnerability to the subjective choices made, a most robust sensitivity analysis was not considered necessary for this study.

To visualize the results and allow for numerical comparisons the estimated vulnerabilities were broken into quintiles (e.g., five categories of vulnerability, each composing 20% of the sample) as well as absolute ranks (i.e., most to least vulnerable). Quintiles were used as the literature does not provide definitive guidance on the best visualization/categorization method. Quintiles allowed for a consistent spread of vulnerability across each municipality. Quantitative results could then be estimated by calculating differences in quintiles and ranks. While other methods could have been used to categorize and visualize the data, such as Jenks Natural Breaks and standard deviations, simple quintiles were used here to facilitate ease of analysis. Given the other sources of uncertainty inherent in estimating relative social vulnerability (see Section 4.3 on limitations below), the use of other categorization/visualization methodologies is not expected to significantly affect the conclusions drawn here. For example, a visual comparison of a Jenks Natural Breaks categorization, which seeks to find the optimal categorization by minimizing the deviation of each category from the category mean, with the quintiles used showed only minor changes in the general spatial patterns of social vulnerability. This is because the categorization method does not affect the estimated relative vulnerability of a location. Furthermore, different visualization/categorization techniques do not affect the conclusions concerning the factors identified as driving social vulnerability.

2.2. Assignment of subjective contribution values

There is a plethora of literature connecting many of the characteristics used here (e.g., wealth, education, employment, asset ownership) to social vulnerability (e.g., Cutter et al., 2009, 2003; Cutter & Morath, 2013; Gall, 2007; le Roux & van Huyssteen, 2010; Soares, Gagnon, & Doherty, 2012; Vincent, 2004). Many of the relationships found in these studies can be viewed as quasi-universal and therefore applicable for this study. However, within the place-based conceptualization of vulnerability, there is a need to re-examine the contribution potential for some variables within the specific South African urban context (see Table 3).

At first, these variables were not assigned a contribution potential (i.e., they were not conceptually linked to contributing to or mitigating social vulnerability), making it difficult to identify whether components composed of only these variables (e.g., a component composed only of age and racial data) would increase or reduce vulnerability. For the 2011 data, only about 15% of components were found to have no explicit link to vulnerability, and approximately 40% of all PCAs run had at least one component that fell into this category. These components typically only explained about 10% of the total variance, though in isolated circumstances they could account for as much as 15%.

To help determine if any of these variables could be assigned a contribution potential, all of the components onto which they was

Table 3
Percent of components that reduce, increase, or have no explicit tie to vulnerability, as well as the resulting subjective contribution potential. A '+' indicates a positive contribution, a '–' indicates a negative contribution, and an 'O' indicates an unqualified contribution.

Variable	Reducing Component	Increasing Component	No Explicit Tie	Subjective Contribution Potential
Under 5 or Over 65	31%	31%	38%	O
Under 5	4%	85%	11%	+
Over 65	71%	17%	10%	–
Average Age	65%	5%	30%	–
Median Age	91%	0%	9%	–
Black	6%	70%	25%	+
Coloured	23%	18%	59%	- or O
Indian/Asian	45%	0%	55%	–
White	93%	0%	7%	–
Afrikaans	44%	11%	45%	- or O
English	91%	0%	9%	+
IsiXhosa	14%	42%	38%	+
IsiZulu	7%	48%	44%	+
Any African Language	4%	71%	26%	+
African Language that is not IsiZulu or IsiXhosa	25%	46%	29%	O
Other Language	52%	0%	47%	–
Housing Rented	43%	0%	57%	–
Housing Rent Free	0%	81%	19%	+
Non-Citizen	71%	0%	29%	–
Moved since the Last Census	90%	0%	10%	–
Recent Arrival	71%	0%	29%	–

loaded were examined (see Table 3). This was done both through visual examination of the variables assigned to each component, as well as through an automated Matlab© program. In each case, the overall contribution potential of each component was determined using only those variables that had direct conceptual ties to social vulnerability. For the vast majority of the variables originally not assigned a contribution potential (i.e., those listed in Table 3), it was found that they were predominately weighted on to components that overwhelmingly either contributed to or mitigated vulnerability. Through this analysis it was possible to subjectively assign a contribution potential to most of these variables based on the contribution potential of the components onto which they were weighted (Table 3 and Annex 1, Table A1). After this subjective assignment of contribution potentials, less than 2% of components had no conceptual tie to social vulnerability, and only 6% of all PCAs run contained such a component.

When no explicit assumptions were made about the contribution potential of variables associated with age, it was found that the average age and median age variables almost always loaded onto components that would be expected to reduce vulnerability, or onto components with no explicit tie to vulnerability (Table 3). Similarly, a high percentage of children under the age of five almost always loaded onto components that would be expected to increase vulnerability. This is likely owing to the fact that within these municipalities, older populations have increased wealth, assets, and education, while a large population of young children is indicative of populations with limited resources. Therefore, variables representing older populations were assigned a negative contribution potential, while variables representing young populations were assigned a positive contribution potential. This somewhat at odds with some previous studies that have suggested older populations are more vulnerable to shocks and stresses owing to their decreased mobility and willingness to leave (e.g., see references in Cutter et al., 2003; Wang & Yarnal, 2012). However, the results here suggest that other contextual factors specific to the urban South African context, such as wealth and resources, associated with age may provide them with the means to be less socially vulnerable relative to younger, poorer populations. This result may suggest that some variables do not have a single association with vulnerability, but may be tied to vulnerability in complex ways that only materialize when multiple individual or household characteristics are combined. Given the divergence in older and younger populations, the variable focused on dependents (i.e., percent of individuals under 5 or over 65) could not be assigned a contribution potential.

Historical legacy issues, like those associated with apartheid, can lead to segregation and social inequalities. Unsurprisingly, variables representing white, Indian/Asian, and English-speaking populations were almost always weighted onto components that would be expected to reduce vulnerability (Table 3). Similarly, variables representing black and African-language speaking populations were predominately loaded onto components that would be expected to increase vulnerability. Conversely, the contribution potentials for variables representing coloured and Afrikaans-speaking populations were less clear as these variables often weighed onto components with no explicit tie to vulnerability. However, further analysis showed that these variables were often loaded inversely onto components with variables representing black and African-language speaking populations. For this reason, the variables representing coloured and Afrikaans-speaking populations were given a negative contribution potential. The inclusion of racial and language characteristics is a deviation from the approach taken by le Roux et al. (2015), who did not use racial variables owning to the disproportionate racial distribution within South Africa. These characteristics were included here because conceptually the contribution potentials determined (e.g., positive for black populations, negative for white populations) are very much in line with what would be expected from the historical legacy issues in South Africa. Furthermore, the rationale cited in le Roux et al. (2015) for not including racial data was based on the fact that country-wide South Africa is predominately black and thus racial data is not spatially differentiated enough. This rationale does not hold in most of the urban municipalities examined here (i.e., the racial data is more spatially differentiated within the municipalities), and so is less relevant in the context of this analysis.

A high percentage of rented properties loaded almost always onto components otherwise expected to reduce vulnerability, while a high percentage of rent-free properties loaded onto components expected to increase vulnerability (Table 3). This is somewhat supported by le Roux et al. (2015) who noted that single, working-class individuals often rent accommodation, while less well off populations live in rent-free properties. Though only incorporated into one data subset, the non-citizen, recently arrived and moved since the last census variables were all found to typically load onto components expected to reduce vulnerability. The negative contribution potential of non-citizens in this study may be owning to the fact that in wealthy urban areas non-citizens are more likely to be educated and employed. However, given these variables were only included in a single data subset, they do not have a significant impact on the average results predominately analyzed below. Further analysis of these variables is not included here as it would require a deep discussion of the socio-economic context of South Africa, which goes beyond the scope of this paper. It would also likely require a multi-variable analysis, as the true contribution potential of these variables is likely linked to how they combine with other variables (e.g., an English speaking non-citizen would be linked to vulnerability differently than an African-speaking non-citizen).

These are clearly subjective choices. Therefore, secondary analyses were conducted where the contribution potentials for demographic and age data were removed and, therefore, the resultant vulnerability was only a function of those variables that had hard conceptual ties to social vulnerability. As noted below, these subjective choices do not have a significant impact on the results and conclusions drawn here.

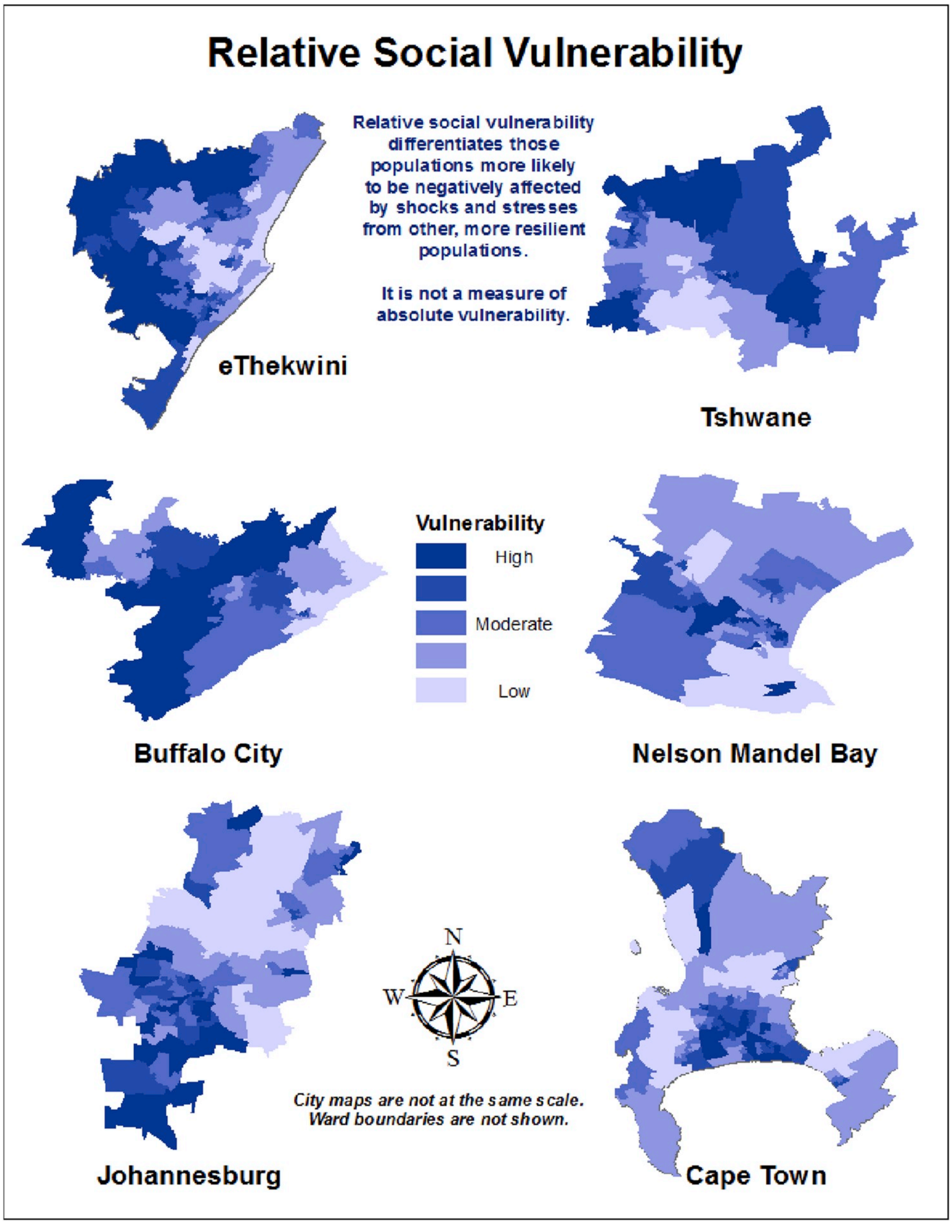

Fig. 2. Schematic map of the spatial variation of the average relative social vulnerability in the six mostly urban municipalities at the ward level.

3. Results

3.1. General results

3.1.1. 2011 census

The PCA reduces the number of variables by approximately four to six times, resulting in two to nine components. The retained components explain between 70% and 88% of the total variance. Generally, data subsets using a larger number of input variables result in a larger number of components. Similarly, a larger number of sub-municipal administrative units usually results in a larger number of components. Conversely, the retained components tend to explain more of the total variance at the ward level than at the small area level.

Social vulnerability varies spatially within all six municipalities (e.g., Fig. 2). A lack of income, wealth, education, assets and employment appears to explain much of this variation (~30–50%). Secondary factors include a lack of access to services, health issues, and demographic/household characteristics. Visual examination of all the components suggests that while some differences exist, the primary factors driving social vulnerability are similar across the six municipalities (i.e., the component composition produced by the PCA is similar for all six municipalities).

In all six municipalities there is an extremely high linear correlation (r^2 typically greater than 0.9) between those administrative units with high computer or car ownership and those with low relative social vulnerability. Other variables highly correlated ($r^2 > 0.8$) with low vulnerability include satellite TV ownership, access to internet from home, and a high monthly income. The only variable highly correlated with high relative social vulnerability is a low monthly income. For individual data subsets and municipalities, other variables can be highly correlated with vulnerability, but the correlations for these six variables are consistent across all data subsets, municipalities and spatial resolutions. Correlations strengthened and more variables became highly correlated with vulnerability as the number of administrative units decreased. For example, only four variables are highly correlated with vulnerability at the small area level, while 13 variables are highly correlated at the ward level. The results are similar whether demographic variables are or are not assigned a contribution potential.

Administrative units with high populations of previously disadvantaged, informal, and non-core family households appear to experience higher relative social vulnerability. As might be expected, administrative units that are predominately white (i.e., greater than 60% of individuals are white) are much more likely to fall into the bottom two quintiles of social vulnerability (97%) than into the top two (0%). Conversely, predominately black administrative units are much more likely to fall into the top two quintiles (69%) than into the bottom two (10%). Administrative units composed predominately of non-core family households are much more likely to fall into the top two quintiles (73%) than the bottom two (5%). Similarly, administrative units composed predominately of informal settlements tend to be the areas experiencing the highest relative social vulnerability, with 93% falling into the top two quintiles. Interestingly, administrative units where more than 60% of households are female-headed can fall into the bottom two quintiles (23%) even though a majority falls into the top two quintiles (54%). This may be because in some administrative units older, white women are acting as the head of household. It is often assumed that female headed households in Africa are more socially vulnerable owing to cultural and/or socio-economic circumstances (Antwi-Agyei, Dougill, Fraser, & Stringer, 2013; Eriksen, Brown, & Kelly, 2005; Flatø, Muttarak, & Pelser, 2017). However, these same circumstances do not apply to older, white female headed households, which are likely composed of widowers with significant resources. For example, these wealthier female headed households are likely not similarly constrained by the same decision-making agency or poverty issues as poorer households, and thus will be linked differently to vulnerability. These results are similar whether contribution potentials are or are not assigned to demographic and age variables.

3.1.2. Changes between 2001 and 2011

As the administrative boundaries for the 2001 and 2011 censuses are not the same, it was not possible to directly compare changes in vulnerability. This would have required re-collating the raw census data so that it conformed to the same set of administrative boundaries for both censuses, which was beyond the scope of this analysis. Furthermore, there are some variables captured in the 2011 census and used in the above analysis that are not available in the 2001 census. Therefore, five additional data subsets containing variables available for both 2001 and 2011 were run through the PCA (Annex 1, Table A2, subsets 16–20). To ensure the vulnerabilities estimated from these data subsets are consistent with those estimated above, the average vulnerabilities from the two sets of data subsets (i.e., subsets 1–15 and subsets 16–20) were compared using the 2011 census data. Across all municipalities and spatial resolutions, the average vulnerabilities are extremely highly correlated ($r^2 > 0.98$), indicating these additional data subsets produced vulnerabilities consistent with the larger analysis conducted above.

The average vulnerabilities for 2001 and 2011 using the five data subsets noted above were examined visually in three municipalities to identify any changes in the general spatial distributions. In all three municipalities, the spatial patterns are quite similar (e.g., Fig. 3). This suggests that the distribution of social vulnerability did not change much between 2001 and 2011, and that the most vulnerable still live in the same places as they did in 2001. However, this does not mean that absolute vulnerability did not change during that decade.

There are some localized areas that appear to have changed a bit more significantly (e.g., south west area of Cape Town). These changes may be driven by the arrival of new populations in these formally sparsely populated areas or through the redistribution of populations owing to the redrawing of the administrative boundaries between the two censuses.

As a first estimate of how absolute social vulnerability may have changed between 2001 and 2011, the data from both censuses were analyzed together for each of the three municipalities. By comparing the vulnerability estimated within a census to the vulnerability estimated across both censuses, it appears that social vulnerability may have decreased between 2001 and 2011 (e.g., Fig. 4). The decrease in vulnerability does not appear to be uniform, but instead it appears that the most vulnerable experienced the largest decrease. However, this analysis does not consider how measures of vulnerability may have changed between 2001 and 2011 (i.e., the same levels of income, assets, and wealth are considered for both censuses). Furthermore, as the SoVI estimates relative social vulnerability, which is not comparable across analyses, it is impossible to say definitely whether or how absolute social vulnerability actually changed between 2001 and 2011. Such an analysis would require some normalization scheme to adjust the variables for changes across the decade. For example, a certain income in 2001 may not be associated with the same level of relative social vulnerability as that income in 2011 owing to factors such as inflation.

While computer ownership is still highly correlated ($r^2 \approx 0.81$) with low relative social vulnerability in 2001, a low monthly income and cell phone ownership are more highly correlated ($r^2 \approx 0.90$). However, the strong correlation between cell phone ownership and social vulnerability decreases significantly in 2011 ($r^2 \approx 0.56$), likely owing to a decrease in cell phone prices and new call plans that increased ownership across all socio-economic classes. This suggests that just because a variable (e.g., computer or cell phone ownership) is a good indicator of relative social vulnerability for one census, does not mean it will remain so, especially when that variable has a firm upper threshold (i.e., asset ownership cannot exceed 100%). Beside cell phone ownership, the general level of correlation between most of the variables used and relative social vulnerability was similar in both 2001 and 2011.

3.2. Sensitivity analysis

All sensitivity analyses were conducted using the 2011 census data, which is considered more robust and inclusive than the 2001 data. Furthermore, the 2011 data is more likely to be used by municipalities in their climate change vulnerability analyses, and therefore is more relevant to future studies.

3.2.1. Data preparation and analytic approach

As discussed elsewhere (Tate, 2012, 2013) both data preparation prior to a PCA and the application of the PCA itself require subjective choices. While it is beyond the scope of this study to test the sensitivity of the results to all possible permutations, the self-consistency of the results is examined for a few permutations. First, the data was prepared using z-type normalization instead of linear normalization, as well as without the removal of outliers or administrative units with low populations, few households, and specific enumeration areas. In terms of PCA application, the data were analyzed using the covariance matrix instead of the correlation matrix. To keep the analysis manageable, not every permutation was run for every combination of municipality and spatial resolution, and each permutation was run separately.

Across all permutations examined, the resultant average vulnerabilities were very similar ($r^2 > 0.98$; less than 7% of administrative units changed quintile or by more than 5% in total rank). However, for some individual data subsets, the results could vary a bit more, with more than 30% of the administrative units changing by a quintile. However, even in these cases only a very small number (< 5%) changed by more than a single quintile or 10% in absolute rank.

Given the small differences in the average vulnerabilities estimated using different data preparation methods and PCA application, it is suggested that these differences are likely smaller than the uncertainty embedded in the underlying approach of the SoVI. Therefore, they are not considered further.

3.2.2. Choice of variables

Owing to the difficulty of obtaining socio-economic data at small spatial scales, especially in the developing world, the proxy indicators used within a SoVI are often selected more owing to availability than to

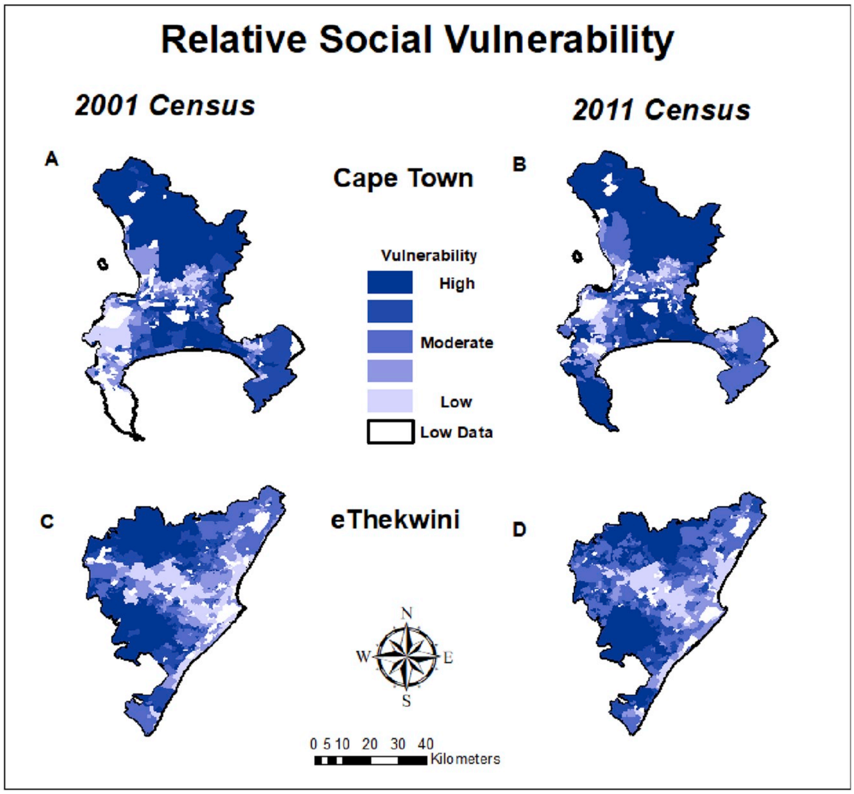

Fig. 3. Average relative social vulnerability estimated using data from the 2001 (A and C) and 2011 (B and D) censuses in Cape Town (A and B) and eThekwini (C and D).

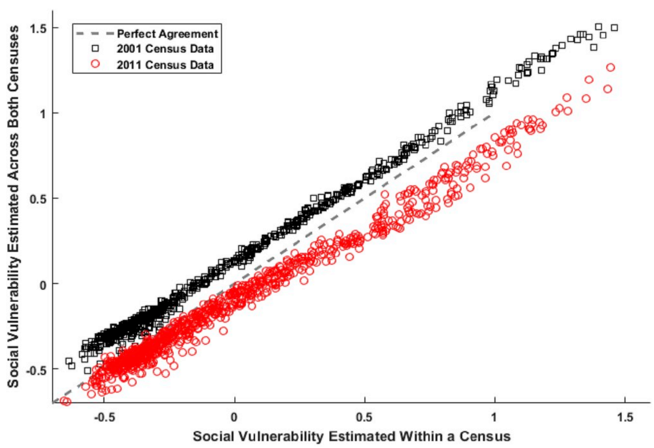

Fig. 4. Social vulnerability estimated across both censuses versus social vulnerability estimated within a census for Cape Town for 2001 (black squares) and 2011 (red circles). Higher values of social vulnerability indicate more vulnerable populations.

their ability to comprehensively characterize social vulnerability. For example, even though the SoVI was derived in the United States using robust census data (e.g., Cutter et al., 2003), it has been applied in various geographies where less robust and comprehensive data is available (e.g., de Sherbinin & Bardy, 2015; Mazumdar & Paul, 2016). While the average vulnerabilities were used in the analysis above, here the vulnerabilities estimated from the individual data subsets are examined to begin to evaluate the sensitivity of the results to the input data.

Generally, the results are somewhat robust across the 15 data subsets for all municipalities and spatial resolutions (r^2 typically greater than 0.75; less than 20% of administrative units differ by more than one quintile across all 15 data subsets) (e.g., Fig. 5). However, for some municipalities, especially at the small area level, almost 40% of the administrative units can experience a maximum difference of more than one quintile (though less than 10% differ by more than two quintiles) across the 15 data subsets. There does not appear to be a spatial pattern to these differences, and therefore it is difficult to determine what could be driving them (Fig. 5). These differences are significantly decreased (i.e., on average less than 6% of the administrative units differ by more than one quintile) if the highest and lowest quintile for each administrative unit are discarded. Unfortunately, identifying the causes of these differences is beyond the scope of this study. Such an analysis would require determining which variables were driving these differences, and then trying to develop causal pathways between those variables and social vulnerability.

While this approach helps gage the sensitivity of the results to the input data, it is somewhat biased as all data subsets were carefully chosen to be inclusive of a range of factors (e.g., assets, education, services, income). What remains unclear is whether the results would differ more if the input variables were chosen randomly. However, random selection is methodically inconsistent as it could result in the inclusion of only a subset of the important and relevant characteristics of social vulnerability, and therefore was not examined.

3.2.3. *Individual municipality vs multi-municipality*

As the SoVI is a relative, and not an absolute, measure, the resultant values of vulnerability are dependent on the data analyzed. For example, the relative social vulnerability of a ward in Cape Town may differ depending on whether data just from Cape Town are included in the analysis, or if data from all six municipalities are included. The scale of analysis is subjective, and will depend on the scale of interest. For example, national policy makers might be interested in which municipalities are the most vulnerable, while provincial or municipal governments may be specifically interested in the spatial distribution of vulnerability within a municipality. Therefore, two additional sets of

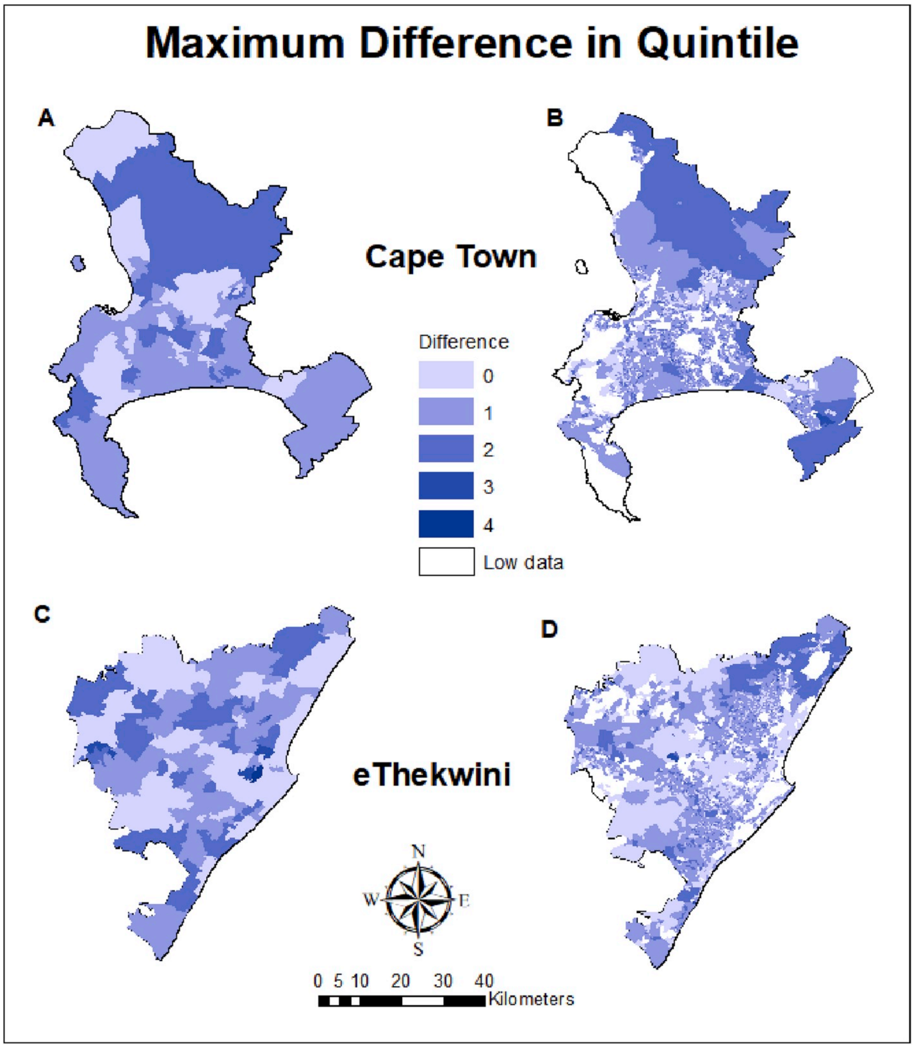

Fig. 5. Maximum difference in quintile from the 15 data subsets for Cape Town (A and B) and eThekwini (C and D) at the ward (A and C) and small areas (B and D) level.

data (i.e., all 15 data subsets) were run through the PCA for each spatial resolution. The first used data from all six municipalities, while the second excluded data from the City of Tshwane (see Table 1, bottom two rows). Aggregating the data across municipalities also helps to ensure that there are no issues with the Ward level data owing to the fact that for some municipalities the number of administrative units is of the same order of magnitude as the number of variables for some data sub-sets. The PCA methodology requires the number of the administrative units to be at least several times the number of input variables for the result to be reliable. This assumption is violated for some data subsets and some municipalities. However, the results presented here demonstrate that this violation of the PCA assumptions does not appear to affect the results.

The general spatial distributions of average vulnerability within a municipality are similar ($r^2 > 0.98$) whether the analysis is conducted within a municipality or across several municipalities. This adds further evidence to the conclusion that the underlying drivers of social vulnerability are similar across the six municipalities. However, the multi-municipality analysis suggests that some municipalities (i.e., Cape Town, Johannesburg, and Tshwane) are relatively less vulnerable than others (i.e., Nelson Mandela Bay, eThekwini and Buffalo City) (e.g., Fig. 6). For example, administrative units in Cape Town, Johannesburg, and Tshwane tend to become relatively less vulnerable (i.e., the quintile into which they fall decreases) when the data from all six municipalities

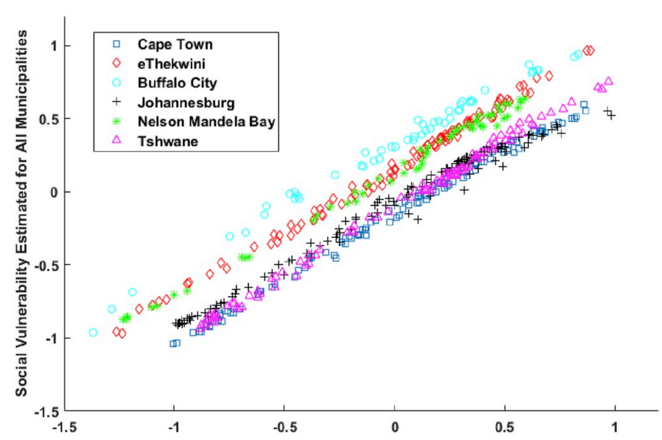

Fig. 6. Average relative social vulnerability at the ward level estimated from a single municipality versus that estimated from all six municipalities for Cape Town (blue squares), eThekwini (red diamonds), Buffalo City (cyan circles), Johannesburg (black plus signs), Nelson Mandela Bay (green asterisks) and Tshwane (magenta triangles). As the data shifts toward the bottom of the figure, it becomes relatively less vulnerable.

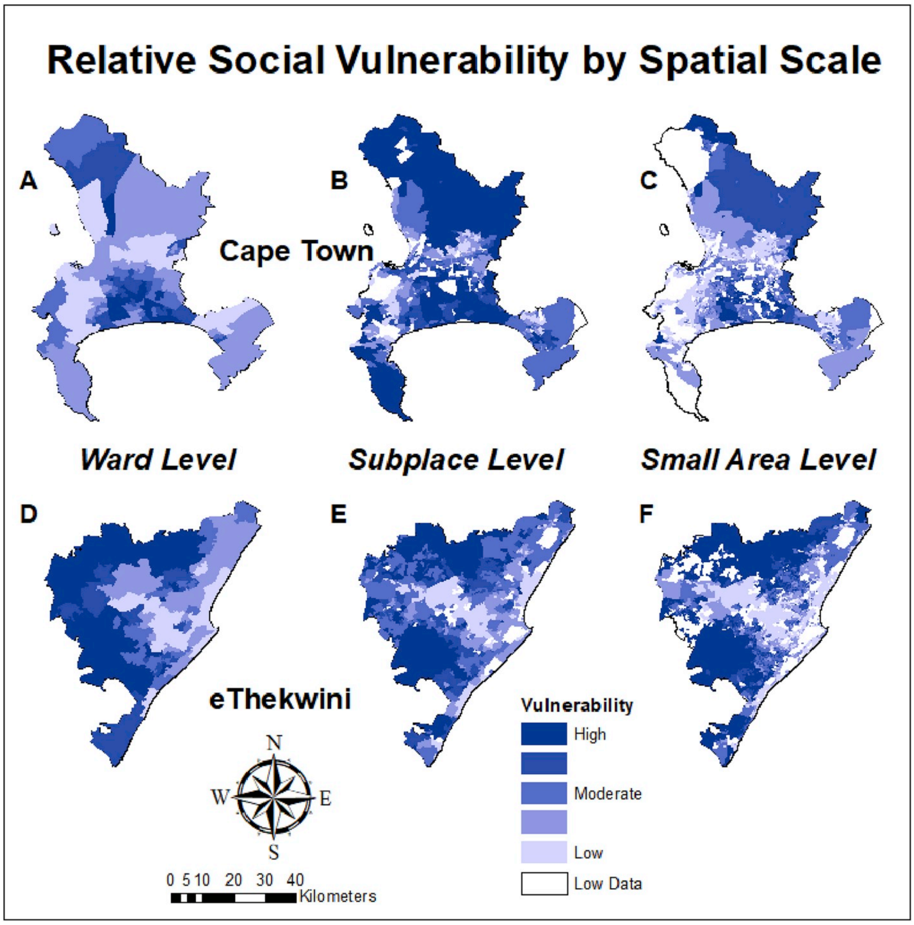

Fig. 7. Average relative social vulnerability for Cape Town (A–C) and eThekwini (D–F) at the ward (A and D), sub-place (B and E), and small area level (C and F).

are analyzed together. This may be because these municipalities are wealthier and have more resources. However, high levels of vulnerability clearly exist within all six municipalities. The results are similar if the multi-municipality data set excluding Tshwane is used.

3.2.4. Spatial boundaries

It may be conceptually appealing to conduct a vulnerability analysis at the smallest spatial scale possible (e.g., small area level for South Africa) as this allows for more spatially differentiated estimates of vulnerability. Furthermore, populations in the smaller administrative units may be more homogenous, allowing the simple statistics used in this analysis to be more representative of those populations. Conversely, with smaller sample sizes, there is greater chance for bias and inconsistency in the data.

Here the spatial patterns of social vulnerability are compared across the three spatial resolutions. Generally, the spatial distribution of social vulnerability is similar, though some differences appear as more spatial variation emerges (e.g., Fig. 7). It is unclear whether these differences are robust enough to justify the use of the small area data. However, according to several decision-makers in eThekwini, the small area level provides them with information at a more usable scale (S. O'Donoghue, pers. comm., May 2, 2018; J. Douwes, pers. comm., May 2, 2018).

3.2.5. Aggregation approach

While PCA is often used to estimate a SoVI, it is not the only way to aggregate the data. Beyond the variance-weighted PCA method used above, two additional aggregation approaches are examined. The first, referred to here as the equal-weighted PCA, simply applies equal weights to all retained components from the PCA when adding them together. The second approach, referred to here as the additive model, does not use PCA at all. Instead, the normalized variables are first added together into sub-indices based on the categories outlined in Table 1. These sub-indices are then normalized, and added together into a measure of vulnerability. The additive model was computed both including and excluding the demographic and age data.

The average vulnerabilities from the variance-weighted PCA are highly correlated with those from the additive model ($0.92 < r^2 < 0.97$) irrespective of whether the demographic and age data are included. The average vulnerabilities are also reasonably correlated with those from the equal-weighted PCA ($0.80 < r^2 < 0.97$). In general, the average vulnerabilities for the additive and equal-weighted PCA models can differ by at least one quintile as compared to the variance-weighted PCA for up to 30% of administrative units, but rarely (< 5%) by more than one. However, this agreement can decrease significantly for individual data subsets and municipalities. For example, the average correlation of the vulnerabilities estimated from individual data subsets is $r^2 = 0.82$ for the additive model and $r^2 = 0.61$ for the equal-weighted PCA. For a few specific data subsets, r^2 can fall below 0.2 for the equal-weighted PCA and below 0.4 for the additive model. Similarly, for some individual data subsets and municipalities, up to 30% and 20% of the administrative units can differ by two or more quintiles for the equal-weighted PCA and additive models, respectively.

The level of correlation between the equal-weighted and variance-weighted PCA results is dependent on the specific components that emerge from individual data subsets. When the individual vulnerabilities are averaged across all 15 data subsets, individual variations decrease in importance resulting in improved correlations. The high correlations between the average vulnerabilities computed by the variance-weighted PCA and the additive model are likely owing to the fact

that the additive model is composed primarily of sub-indices associated with wealth, assets, income and education, the primary factors driving vulnerability in the variance-weighted PCA. Interestingly, when a PCA is run on eight of the nine sub-indices (excluding the Health sub-index), the analysis produces a single component for Cape Town, eThekwini, and Nelson Mandela Bay. Even in Buffalo City, Johannesburg and Tshwane, where the PCA produces two components, all eight of the sub-indices are loaded onto the first component. This suggests that these eight sub-indices are somewhat correlated within these municipalities.

4. Discussion

4.1. Choosing the best approach

Without an objective measure of social vulnerability for comparison, it is difficult to determine the best way to construct a SoVI. For example, it is unclear whether the variance-weighted PCA provides more accurate estimates than the equal-weighted PCA and additive models. Similarly, it is unclear whether the first data subset, which contains 44 variables, produces more accurate estimates than the 15th, which only includes 11 variables. Going further, it is unclear whether the amount of effort required to conduct the variance-weighted PCA improves our understanding of the spatial patterns of relative social vulnerability over simply mapping single asset ownership (e.g., computer ownership) or income. For example, the spatial patterns of the average vulnerabilities estimated from the variance-weighted PCA and for the percent of the working age population making less than R800 per month are quite similar for both 2001 and 2011 (e.g., Fig. 8). Therefore the spatial patterns estimated (e.g., Fig. 8) follow closely those areas where poor populations currently live. Furthermore, when the maps from Cape Town were shared with city officials, these officials noted the maps conformed quite well to their implicit understanding of relative social vulnerability within the city (A. Davison, pers. comm., February 1, 2018).

While the results are fairly robust across a wide range of subjective choices for the average vulnerabilities, the results can differ significantly (i.e., differences of more than two quintiles) for individual data subsets and aggregation approaches. Such differences can be important when interpreting the results or using them to inform decision-making. Visualizing these differences (e.g., Fig. 5) can help highlight areas where the relative level of vulnerability is less certain or variable. However, given the challenges of determining the best way to craft a SoVI, it might be better to use a multi-method approach than a single methodology (similar to the multi-model approaches used for climate projections). Through the use of multiple methods, both internal consistency and areas experiencing greater uncertainty can be identified. However, further analysis may be necessary to identify the best way to combine the results of multiple methods given that the results of a PCA are only relative to each other.

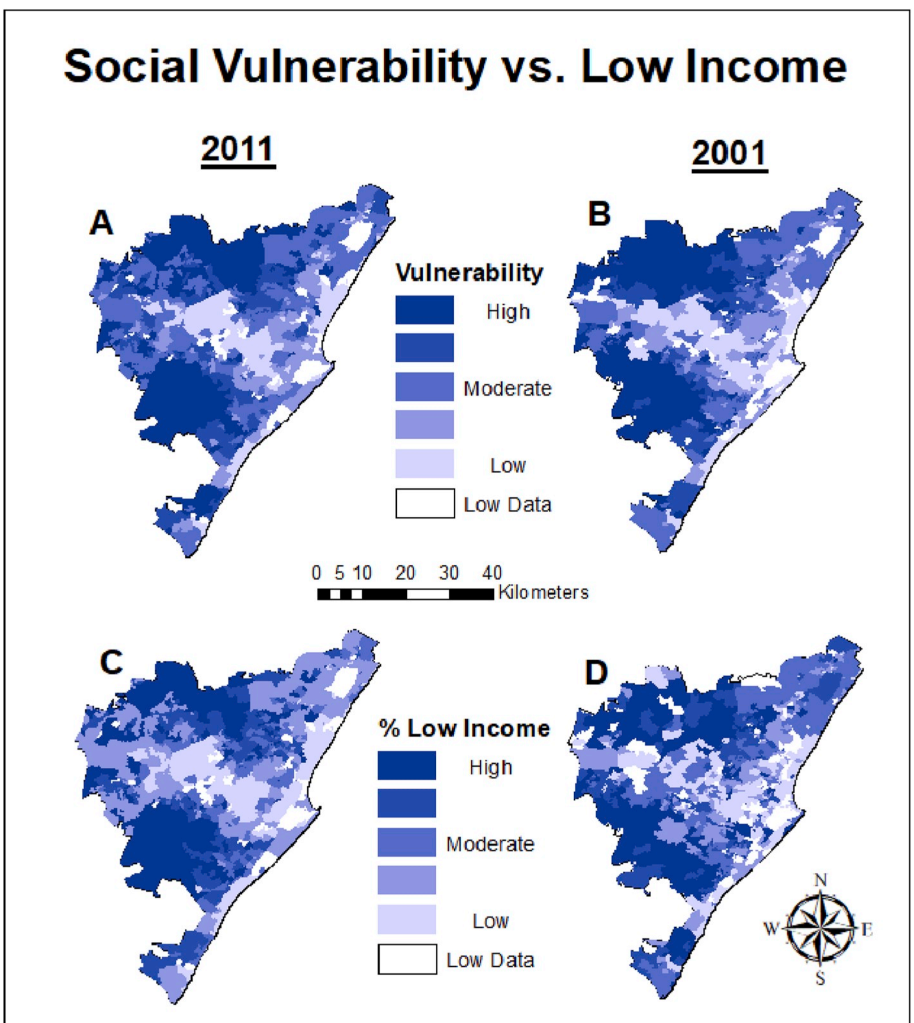

Fig. 8. Average relative social vulnerability (A and B) and percent of the population between 25 and 65 making less than R800 per month (C and D) for 2001 (B and D) and 2011 (A and C) for eThekwini. Sub-plots should be compared within a year (i.e., from top to bottom of figure).

4.2. Policy relevance

Influencing policy and decision-making was not an explicit objective of this work, as this would have required significantly greater interaction with decision-makers in co-producing these maps. However, such maps have potential policy relevance, as demonstrated by the development of similar maps by municipal governments and national agencies (e.g., City of Tshwane, 2015; le Roux et al., 2015). Furthermore, the Council for Scientific and Industrial Research (CSIR) of South Africa continues to refine its methodology for developing a national SoVI (le Roux et al., 2018; A. le Roux, pers. comm., September 19, 2017) with the intent to influence policy decisions. The results presented here can provide additional evidence related to the robustness and limitations of such an approach. The maps could also provide municipal decision-makers with additional information on the spatial distribution of social vulnerability. To facilitate the transfer of this information, simple four page fact sheets outlining the key findings and providing illustrative maps were created for each municipality and shared with select decision makers. While the response to these fact sheets goes beyond the scope of this paper, these fact sheets helped Cape Town integrate the results into an ongoing resilience assessment (G. Morgan, pers. comm., April 16, 2018).

4.3. Limitations

While this study can suggest areas where social vulnerability is relative higher, it is not without limitations, many of which are applicable to most efforts to estimate social vulnerability. One of the biggest limitations is the lack of an objective measure of social vulnerability with which to compare and confirm the results. While the results appear to be reasonably self-consistent, self-consistency is not the same as being correct (i.e., the results could be consistently wrong). Furthermore, while the data from the South African census is fairly robust, it likely contains inconsistencies and biases. Perhaps more importantly, the census does not contain information on all the factors important for estimating social vulnerability. For example, the health data contained in the census tends to emphasize characteristics found in older populations, and was, at times, somewhat correlated with these older populations. If different health data (e.g., malnutrition, stunting) could be obtained at the required spatial resolution, it might be possible to better assess the health component of social vulnerability. Similarly, the data used here did not include the limited mobility of older populations found in other studies, and therefore may have missed this important dimension of social vulnerability. Furthermore, a number of studies have shown that hard to measure characteristics, such as social capital, governance structures, and kinship networks are incredibly important to understanding vulnerability (e.g., Adger, 2003; Batterbury & Mortimore, 2013; Brooks, Adger, & Kelly, 2005; Chu, Anguelovski, & Roberts, 2017; Granderson, 2014; Leck & Roberts, 2015; Pelling & High, 2005; Roberts & O'Donoghue, 2013; Tompkins, Adger, & Brown, 2002). However, data on these aspects of vulnerability do not exist within these municipalities. Acquiring such data would require a huge effort to qualitatively survey these urban populations. Therefore the results shown here should only be considered as one potential estimation of relative social vulnerability. Furthermore, some of the data used does not vary continuously. For example, some of the data (e.g., percent of informal dwellings) were more bifurcated in distribution, with values clustering close to 100% or 0%, especially at the small area level. Such data is somewhat inconsistent with the PCA approach, which depends on linear correlations.

This analysis also looks at most variables in isolation, whereas the contribution potential of some characteristics might change in combination with other characteristics. For example, if information on female-headed households was combined with other demographic or wealth data, the resultant variable might have a more direct tie to vulnerability. Another limitation is that all three of the aggregation approaches assume that the variables are at least somewhat compensatory, in that a low level in one can be compensated by a high level in another. These aggregation approaches also fail to account for the complex interactions and non-linear thresholds that likely exist. Furthermore, the sensitivity analysis did not examine every possible permutation.

This paper also defines social vulnerability as a generic concept, which may not be applicable to specific hazards. For example, what makes a person vulnerable to a drought might be different than what makes them vulnerable to a flood or a veld fire. Furthermore, the variables identified here were done so within an urban context, and might not be as appropriate for use in rural areas. Finally, as vulnerability is dynamic and varies at different scales and for multiple stresses (e.g., Downing et al., 2006; Leichenko & O'Brien, 2002; Reid & Vogel, 2006; Ziervogel, Bharwani, & Downing, 2006), the results presented here, like the results for most vulnerability indices, should be viewed more as descriptions of existing conditions than as predictive tools (Cutter et al., 2008).

5. Conclusions

Social vulnerability varies spatially in the six mostly urban South African municipalities examined here. These spatial variations are driven primarily by a lack of income, wealth, education, assets and employment, and secondarily by a lack of services, health issues, and demographic/household characteristics. For example, asset ownership (e.g., computer, cell phone, car) is well correlated with low social vulnerability, while a low monthly income is well correlated with high social vulnerability. However, there is some evidence that single asset ownership may not be a consistent predictor of relative social vulnerability over time.

The spatial patterns of relative social vulnerability are generally similar in 2001 and 2011, suggesting the most vulnerable still live in the same areas. This may be because areas with high populations of previously disadvantaged, informal, and non-core family households tend to be those that experience higher social vulnerability. Thus, while dynamic population growth continues within these urban areas, the spatial distributions observed may be at least partly a continued result of the historical spatial planning legacy of apartheid. Conversely, there is some evidence that people in general may have become less vulnerable between 2001 and 2011. Further analysis is needed to verify this.

A sensitivity analysis demonstrated that the average results (i.e., averaged across the 15 data subsets used) are robust across different data preparation and PCA methodologies. Similarly, the same general spatial patterns of vulnerability emerge irrespective of whether the data is analyzed within a municipality, across all six municipalities or using different administrative boundaries. Furthermore, the average results are fairly robust across the aggregation methods examined. However, when individual data subsets are used, the resultant vulnerabilities can be quite sensitive to both the input data and the data aggregation method. This may suggest that using a multi-method approach to estimate a SoVI should be a best practice, similar to what is done with climate models. However, further research is necessary as to how best to combine the results of multiple methods.

Finally, given the challenges and limitations associated with developing a SoVI, it is unclear whether the amount of effort required to conduct a variance-weighted PCA, as was done here, improves our understanding of the spatial patterns of social vulnerability. For example, the spatial patterns of the variance-weighted PCA results and of the percent of the working age population making less than R800 per month are quite similar. On the other hand, detailed analyses such as a PCA, which incorporates a range of population and household characteristics, may generate a higher level of confidence than a single characteristic analysis.

Acknowledgements

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Annex

Table A1
Definition of Variables. Note: HH = household and I = Individual.

Variable	Abbr.	Definition	Contribution to Vulnerability	Level
Average Annual Income	Avg Inc	Average annual income. The center of the income brackets are used in this calculation. For the highest income bracket, the lower bound is used.	–	HH
Low Income	Low Inc	% of population between 25 and 65 years of age making less than R800 per month	+	I
High Income	Hi Inc	% of population between 25 and 65 years of age making R25,600 or more per month	–	I
Computer	Computer	% of households who own a computer	–	HH
Car	Car	% of households who own a motor car	–	HH
Satellite TV	Sat TV	% of households who own a satellite television	–	HH
Cell Phone	Cell Ph	% of households who own a cell phone	–	HH
Internet from Home	Int Home	% of households who primarily access the internet from home	–	HH
No Internet	No Int	% of households who have no access to internet	+	HH
Poor Education	Poor Edu	% of population 20 years of age or older that did not finish primary school	+	I
Good Education	Good Edu	% of population 20 years of age or older that has a greater than 12 grade education	–	I
School Attendance	School	% of the population between 6 years of age and 18 years of age who are currently attending school	–	I
Head of Household Employed	HofHH Emp	% of head of household who are employed	–	HH
Working Age Employed	Empl	% of individuals between the ages of 25 and 65 who are currently employed	–	I
Working Age Unemployed	Unempl	% of individuals between the ages of 25 and 65 who are currently unemployed	+	I
Flush Toilet	Toilet	% of households with access to a flush toilet, either connected to a sewer system or a septic tank	–	HH
Piped Water Inside Dwelling	Piped Water	% of households who have access to piped water within their dwelling	–	HH
Cooking Fuel	Cooking	% of households using something besides electricity or gas for cooking	+	HH
Trash Removed	Trash	% of households who have their refuse removed by local authority/private company	–	HH
Access to City Water	City Water	% of households with access to a regional or local water scheme operated by a municipality or other water service provider	–	HH
Lighting Source	Lighting	% of households using something besides electricity or gas for lighting	+	HH
Mail Delivered	Mail	% of households with mail delivered	–	HH
Communication Difficulty	Comm	% of population older than 5 years of age with at least some difficulty communicating	+	I
Mental Difficulty	Mental	% of population older than 5 years of age with at least some difficulty remembering or concentrating	+	I
Physical difficulty	Phys	% of population older than 5 years of age with at least some difficulty walking or climbing stairs	+	I
Self-Care Difficulty	Self Care	% of population older than 5 years of age with at least some difficulty taking care of themselves	+	I
Population Density	PopDen	Population Density	+	I
Average Household Size	HH Size	Average household size. Households with more than 10 people are included in average as having 10 people.	+	HH
Households with > 6 people	HH > 6	% of households with more than six people	+	HH
Informal Dwellings	Infr Dwel	% of dwellings that are informal	+	HH
Female Headed Households	FM HH	% of households that are headed by females	+	HH
Non-Core Family Members	Non-Core	% of population living in a household who is not a member of the core family (not spouse, child, or parent)	+	I
Father Alive	Father	% of children under 15 years of age whose father is still alive	–	I
Mother Alive	Mother	% of children under 15 years of age whose mother is still alive	–	I
Under 5 or Over 65	U5O65	% of population under 5 years old or 65 years of age or older	O	I
Under 5	U5	% of population under 5 years old	+	I
Over 65	O65	% of population 65 years of age or older	–	I
Average Age	Avg Age	Average age of the population	–	I
Median Age	Med Age	Median age of the population	–	I
Black	Black	% of the population that is black	+	I
Coloured	Coloured	% of population that is coloured	- or O	I
Indian/Asian	Indian	% of population that is Indian or Asian	O	I
White	White	% of population that is white	–	I
Afrikaans	Afrikaans	% of population whose primary language is Afrikaans	- or O	I
English	English	% of population whose primary language is English	–	I
IsiXhosa	IsiXhosa	% of population whose primary language is IsiXhosa	+	I
IsiZulu	IsiZulu	% of population whose primary language is IsiZulu	+	I
Any African Language	African	% of population whose primary language is any African language	+	I
African Language that is not IsiZulu or IsiXhosa	Afr no	% of population speaking an African language that is not IsiXhosa or IsiZulu	+	I
Other Language	Other Lan	Language listed as NA	O	I
Housing Rented	Rented	% of households living in rented housing	–	HH
Housing Rent Free	Rent Free	% of households living in rent free housing	+	HH
Non-Citizen	Non-Citiz	% of population that is not a South African citizen	–	I
Moved since the Last Census	Moved	% of population that has moved since the last census. For the 2001 census this is 1996, while for the 2011 census this is 2001.	–	I
Recent Arrival	Recent	% of population that moved into South Africa since 2000	–	I

Table A2
Variables Used in Each Test.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Avg Inc	x	x	x	x	x			x			x		x	x		x		x	x	
Low Inc	x	x	x	x	x		x	x			x	x		x		x	x			x
Hi Inc	x					x			x	x			x							
Computer	x	x	x	x	x	x	x			x		x			x	x	x			x
Car	x	x	x	x	x	x	x		x	x	x		x		x					
Sat TV	x		x	x	x			x	x	x		x		x						
Cell Ph	x	x	x	x	x			x			x	x		x		x	x	x	x	x
Int Home	x				x	x		x		x			x							
No Int	x	x	x	x			x		x		x				x					
Poor Edu	x		x	x	x		x	x			x	x		x		x	x	x		x
Good Edu	x	x				x			x	x			x		x				x	
School	x		x																	
HofHH Emp	x		x	x					x			x					x			
Empl	x	x	x			x			x	x			x		X				x	
Unempl	x			x	x		x	x			x	x				x	x			x
Toilet	x		x	x	x	x	x		x	x		x			x	x	x			
Piped Water	x	x	x	x		x	x			x			x		x				x	
Cooking	x	x	x	x		x	x	x		x	x	x		x						
Trash	x		x	x	x	x	x		x	x			x	x		x		x		x
City Water	x		x	x				x					x							
Lighting	x	x	x	x	x			x			x	x			x	x	x		x	x
Mail	x		x	x	x			x	x		x		x	x						
Comm	x		x									x					x			
Mental	x		x									x					x			
Phys	x		x										x							
Self Care	x		x										x							
PopDen	x	x		x						x	x		x		x				x	x
HH Size	x			x		x	x			x		x			x					
HH > 6											x			x						
Infr Dwel																			x	x
FM HH	x		x	x		x	x			x	x	x		x			x	x	x	x
Non-Core	x			x	x					x	x		x		x	x			x	
Father	x								x											
Mother	x		x	x							x									
U5O65	x	x												x				x		
U5			x	x	x	x	x	x		x		x				x	x			
O65			x	x	x	x	x	x	x	x	x	x				x	x			
Avg Age														x				x	x	
Med Age	x	x		x					x		x		x							x
Black	x	x						x	x			x					x		x	

Coloured	x	x						x	x			x					x		x	
Indian	x																			
White	x	x						x	x			x					x		x	
Afrikaans	x				x	x	x						x			x				
English	x			x	x	x	x						x			x				
IsiXhosa	x																			
IsiZulu	x																			
African	x				x	x	x		x				x			x				
Afr no				x																
Other Lan									x											
Rented					x											x				
Rent Free					x											x				
Non-Citiz				x																
Moved				x																
Recent				x																
TOTAL	**43**	**17**	**26**	**30**	**21**	**17**	**17**	**16**	**18**	**17**	**17**	**19**	**18**	**12**	**11**	**17**	**16**	**8**	**14**	**11**

An 'x' indicates the variable was used in a test.

The light shading differentiates different categories of variables.

Tests 1-15 were run for 2011 data, while tests 16-20 were run for both sets of data.

Blacked out boxes indicate that variable was not available for the 2001 census.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2019.02.012.

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